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Environmental Policy and Employment: The Effect of the Regional Greenhouse Gas Initiative on the Labor Market

Kelly-Anne Moffa
kelly-anne.moffa@uconn.edu

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Abstract

This paper estimates the impacts that the Regional Greenhouse Gas Initiative, implemented in 2009, has had on labor market outcomes within the policy region. The Regional Greenhouse Gas Initiative is a carbon cap-and-trade program that consists of ten states in the Northeast. Using a difference-in-difference framework, I found that, overall, there was no significant impact on the annual employment growth rate because of RGGI. When broken down into industry-specific effects, most industries still had no significant employment effects, although the mining industry did see a weakly significant 0.09 percentage point decrease in its annual employment growth rate. These estimates are based on the time period of 2001 – 2018. This paper provides initial evidence on how the Regional Greenhouse Gas Initiative has impacted labor market outcomes.

Section 1 – Introduction

In recent years, the impacts of environmental regulations have become more heavily debated. As a central issue throughout the most recent presidential election, the different concerns regarding environmental policies were countered by the benefits that advocates proposed. Among the highest concerns was the impact that environmental regulations will have on employment. This concern was the highlight of former President Trump's reasoning for leaving the Paris Climate Agreement, citing that regulations would increase costs for companies, either causing mass layoffs to occur or the shutdown of entire firms (Borchers and Phillips 2017). However, other politicians, such as Rep. Ocasio-Cortez and other supporters of the Green New Deal, claim that environmental regulations can strengthen the economy by creating new, green jobs (Kurtzleben 2019). The effects of environmental policies on employment largely depend on their structure and implementation. This paper seeks to inform the public and policymakers about the effect that environmental policies can have on employment through examining the employment impact of the Regional Greenhouse Gas Initiative (RGGI).

RGGI began in 2009 as a regional cap and trade system agreed on by ten Northeast states in the US (Elements of RGGI 2021). RGGI is the first mandatory, market-based CO_2 emissions reduction program in the United States. Each year, auctions are held in these states for electric power plants to purchase allowances in order to emit a certain number of tons of CO_2 per year. The number of allowances is capped to a certain number each year within the region. This cap has been adjusted over time to decrease emissions and account for allowances that firms have banked for future use. States also have the discretion to use the revenues from their CO_2 auctions however they see fit. Most use the revenue for energy efficiency projects (The Investments of

RGGI Proceeds in 2018). While RGGI only effects the utilities labor market directly, this allows me to observe the pass-through effects of environmental policies to other sectors that may be indirectly impacted by the regulations and hold a larger share of employment.

I utilize a simple labor market model to explain the theory behind my empirical analysis. This model illustrates the various effects that environmental policies can have on employment. The first is the factor substitution effect. The cap-and-trade policy may increase labor demand as firms substitute away from energy towards labor. However, the policy may also decrease labor demand. RGGI could increase a firm's marginal cost and therefore decrease its output. This is called the output effect. Another effect comes from the increase in market price after the shift in the market supply curve. Lastly, these effects could be minimized depending on what states do with their auction revenues. Since there are multiple effects that can impact the labor market outcomes of this cap-and-trade policy, the overall effect determined by the theoretical model is ambiguous. Therefore, further empirical analysis is necessary to determine the actual size of the effect.

My empirical methods are most closely related to Greenstone (2002), Yamazaki (2017), and Huang and Zhou (2019). I use industry and state-level data to show the changes in employment before and after RGGI was implemented. These data are from the Bureau of Economic Analysis and they provide information on employment numbers and wage. My treatment region is comprised of all states that were in RGGI from 2009 – 2018, excluding New Jersey. My control region consists of states that are in the Pennsylvania-New Jersey-Maryland energy market that are not also in RGGI. The time period of my data is from 2001 – 2018. I use a difference-in-difference equation to estimate the impact that RGGI had on employment growth. I also use various fixed effects and state covariates to attempt to control for other events that may have happened at the same time as RGGI and impacted employment. I use a difference in difference approach to estimate both the overall impact of RGGI and industry-specific impacts.

The results indicated that RGGI had no significant impact on employment overall for the policy region. When broken down by industry, RGGI had a weakly significant negative impact on the mining industry. Based off of my results, annual employment growth rate in the mining industry decreased by 0.09 percentage points because of RGGI. This result is consistent with previous studies that have shown that energy intense industries are more vulnerable to impacts from environmental policy (Yamazaki 2017). My results also return some unexpected results, such as a significant negative impact on the finance industry and a significant positive impact on the accommodation services industry. These results may indicate that different specifications or more data are required to control for outside effects more accurately.

The rest of this paper proceeds as follows. *Section 2* covers the history of RGGI, its construction, implementation, and effects. *Section 3* examines previous papers that have been written about RGGI and the effects of environmental regulation on the labor market. *Section 4* identifies the theoretical labor model that shows how RGGI would impact employment. *Section 5* explores the empirical analysis and I explain my data, methods, results, and robustness checks. Lastly, in *Section 6* I discuss the conclusions that arise from this analysis.

Section 2 – Overview of RGGI

In 2003, the governors of nine states gathered to discuss the possibility of starting a regional cap-and-trade system to curb greenhouse gas emissions. Seven of the original nine states signed a Memorandum of Understanding (MOU) in 2005 that outlined the framework of the Regional Greenhouse Gas Initiative (RGGI). The remaining two states, as well as Maryland, signed the MOU in 2007, and RGGI went into effect on January 1, 2009, with Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New Jersey, New York, Rhode Island, and Vermont as member states. In 2012, New Jersey withdrew from RGGI, but rejoined in 2020. Lastly, Virginia joined in 2021.

RGGI is an agreement between eleven states in Northeast of the United States to reduce carbon dioxide (CO_2) emissions from the region. It is the first mandatory, market-based CO_2 emission reduction program in the United States (Elements of RGGI 2021). Figure 1 shows a map of the RGGI states. Through independent regulations, these states have agreed to moderate CO_2 emissions from their states in order to comply with the RGGI Model Rule set through the collaboration of members. Within the RGGI states, fossil-fuel-fired electric power generators with a capacity of 25 megawatts or greater are required to hold allowances equal to their CO_2 emissions over a three-year period (Elements of RGGI 2021). Firms buy allowances at regional auctions and can trade them in secondary markets with other firms. One allowance is equal to one US ton of CO_2 emissions.

Figure 1: Map highlighting the member states of RGGI. New Jersey and Virginia are highlighted in light yellow because they joined most recently. Source: RGGI Project Series (https://www.rggiprojectseries.org/states)

Each state sets independent regulations that follow the RGGI Model Rule. The involved states have established CO_2 Budget Trading Programs that limit emissions of CO_2 from electric powerplants, issue CO_2 allowances, and establish participation in regional CO_2 allowance auctions (Elements RGGI 2021). All of the allowances administered by the state budgets add up to the total RGGI cap. RGGI caps have been adjusted since the inception of the program to reflect trends. At the beginning of the program in 2009, the cap was 188 million allowances. This cap has been adjusted over time to decrease emissions and account for allowances that firms have banked for future use. In 2021, the adjusted cap is just over 100 million allowances.

In RGGI auctions, there is a cost containment reserve (CCR) that consists of extra allowances available for purchase if auction prices reach a certain point. This was created in order to keep allowance prices below a certain level. Moving forward, this price will increase as the number of allowances decreases to help minimize CO_2 emissions over the years. The trigger price in 2020 was $10.77 and in 2021 it is $13 (Elements of RGGI 2021). There is also an emission containment reserve (ECR) that was first implemented in 2021. The states will withhold allowances to create additional emissions reductions and to make sure that auction prices do not fall below a certain level. This price will also increase each year. For 2021, the ECR trigger price is $6.00 (RGGI 2016 Program Review 2017, 3).

Each state also decides what to do with the revenue from their auctions. Many of the investments go to energy bill assistance, increasing energy efficiency, and funding renewable energy. In the region, 38% of RGGI investments go to energy efficiency projects, 19% to clean and renewable energy infrastructure, 20% to greenhouse gas abatement, and 16% to direct bill assistance (The Investments of RGGI Proceeds in 2018, 5). RGGI, Inc reports that these investment actions prevented 273,217 short tons of CO_2 from being emitted into the atmosphere in 2018 and saved $113,711,413 on energy bills.

Overall, the intent of RGGI is to decrease CO_2 emissions. A report from RGGI, Inc states that annual average emissions in the RGGI-region decreased by 45.3% from 2008 – 2017 (RGGI 2019, 7). However, exactly where these reductions come from is debated. A study by Kim and Kim (2016) found that coal to natural gas switching was accelerated by RGGI in the policy region, which may have contributed to emission reductions because natural gas emits less CO_2. There have also been studies that show these reductions came from leakage of electricity production to powerplants outside of the RGGI region. Ohio and Pennsylvania are considered “leaker states”, i.e., places where powerplants moved to after regulations increased. A study found that reduced coal-fired generation in RGGI-states was compensated for by increased generation in regions of Pennsylvania and Ohio (Fell and Maniloff 2018). It is estimated that CO_2 emissions increased by 4.5 million tons per year in states where electricity generation leaked to and RGGI-states CO_2 emissions decreased by 8.8 million tons per year, for an aggregate decrease of 4.3 million tons per year (Fell and Maniloff 2018). So, while leakage may decrease the real decline in CO_2 emissions, RGGI has still been effective at achieving its overarching goal of reducing emissions.

There are other impacts of RGGI that have not been extensively studied. Labor market effects and impact on regional growth have been studied for other environmental policies, such as the Clean Air Act Amendments, European Emissions Trading System, and the British Columbia carbon tax, but not for RGGI. Therefore, in order to gain a holistic view of the impact that RGGI has had, this paper seeks to analyze how RGGI has impacted annual employment growth for the policy region overall and for specific industries.

Section 3 – Literature Review

An increasing body of literature has been written on environmental regulations and their effects on employment. Each study approaches the issue in a unique way and there are no consistent results for or against the regulations. In this literature, the impact of environmental policies is related to the market conditions, sectors affected, and the structure of the policy itself. Some of the papers find positive effects of environmental policy on labor market outcomes, while others find a small negative effect or no effect (Berman and Bui 2001; Greenstone 2002; Morgenstern, Pizer, and Shih 2002; Abrell, Ndoye Faye, and Zachmann 2011; Yamazaki 2017; Marin, Marino, and Pellegrin 2018). When examining RGGI, there has been ample research on the impact of RGGI as it relates to decreasing greenhouse gas emissions and the leakage of energy generation (Kim and Kim 2016; Fell and Maniloff 2018; Huang and Zhou 2018; Chan and Morrow 2019). However, the impact that the CO_2 emissions trading market has had on the labor market has not been studied. These papers provided me with insight into the way that environmental regulations have impacted employment and how this may relate to the way RGGI has influenced the labor market.

Section 3a of my literature review focuses on studies that have examined the effects of other environmental policies on labor market outcomes. Section 3b discusses papers that have looked at the effect of RGGI on energy and emission outcomes.

Section 3a

In Yamazaki (2017), the researcher finds that the British Columbia (BC) carbon tax generated a 0.74% annual increase in employment over the years that the carbon tax was implemented. They came to this conclusion through the aggregation of the tax's direct effect on employment within industries and the effect that the redistribution of the tax revenue had on employment. Through trade intensity and emission intensity interaction terms, they were able to view the output effect of the carbon tax. They measured the redistribution effect of the tax by interacting BC's overall greenhouse gas emissions from 2007 with the carbon tax. The coefficients that measured the output effect were negative, which aligned with their theoretical model. In this model, Yamazaki speculated that the BC carbon tax would increase marginal costs for industries and reduce their output, therefore reducing the number of employees needed to achieve the new level of output. However, since the BC carbon tax is revenue neutral, the researcher accounted for a redistribution effect in their analysis. In their theoretical model, Yamazaki illustrated that the redistribution effect would impact both labor supply and demand. If the tax revenue is redistributed to residents, as consumers they can spend their additional income on goods and services, increasing the goods and services' demand, and therefore increasing the demand for labor to supply those goods and services. Supply of labor is increased because revenue-recycling "decreases distortion in the labor market" (Yamazaki 2017, 201). The substitution effect suggests that if an industry can easily switch from energy to labor in order to lessen the burden of the tax, they will do so and therefore increase labor demand. Yamazaki's coefficient for the redistribution effect is positive throughout their various specifications, which aligns with their theoretical model. They plotted the change in employment by industry, which shows that industries that are both emission and trade intense will see a decrease in employment from the carbon tax, while industries that are either emission intense or trade intense (or neither) may see no employment effect or employment growth. When they aggregated the average effect for each industry, they found an overall positive impact on employment in BC from the carbon tax.

In RGGI, each individual state determines what is done with their CO_2 permit auction revenue, so my paper does not focus on the potential redistribution effects of RGGI revenue. However, that would be beneficial to explore as a more in-depth analysis of the impacts of RGGI on individual states within the RGGI region. The results from Yamazaki (2017) also show that, since the positive employment benefits come from the redistribution of the tax revenue, redistribution should be an avenue considered for future environmental policies or revisions of current ones.

In Berman and Bui (2001), the researchers looked at the impacts that air quality regulation from the Clean Air Act had on employment in the manufacturing sector in Los Angeles. They found that the employment effects of compliance with new regulations and increased stringency of existing regulations were zero, even when exit and dissuaded entry effects were included. When estimating the cumulative effects of 12 years of air quality regulation, Berman and Bui (2001) estimate that the regulation caused anywhere from 9,600 jobs lost to 12,300 jobs gained during the regulation time period. They posit that these small effects come from three factors. The first is that regulations apply disproportionately to capital-intensive factories with relatively little employment. The second is that the affected plants sell to local markets where their competitors face the same regulations that they do, so the regulations will not decrease sales. The final factor is that abatement inputs complement employment. The researchers use two mechanisms to show the effect that regulations have on employment: the output elasticity of labor demand and the marginal rates of substitution between pollution abatement activity and labor. The output effect is largely assumed to be negative, though if compliance with the regulation could be achieved through an investment that reduces marginal costs, the effect could be positive. The substitution effect is ambiguous and depends on the type of abatement strategy assumed. If a factory adopts "end-of-pipe" technologies to abate pollution, labor will be complemented. However, if a factory improves the production process, the demand for labor will be reduced due to the skills bias of technological change.

Another important aspect that the researchers examine is the entry and exit of plants that is induced by environmental policy. They include this in their analysis by using comparison regions to represent the pattern of employment change that would have occurred in the South Coast without regulations. Compiling these patterns with employment trends in continuing plants, they were able to estimate the effects of regulation on employment including forced exit of plants and dissuaded entry. Again, they found no large negative employment effects.

Berman and Bui (2001) suggest that a possible explanation for the small employment effects is that the regulations target capital intensive industries with relatively little employment. Since RGGI only impacts electricity generating power-plants, this may also be an explanation for small employment effects caused by RGGI. They also discuss how regulations impact an entire industry as opposed to individual firms; therefore, output-demand from each individual firm will only be slightly reduced because an industry's product demand curve is less elastic than an individual firm's demand curve.

Greenstone (2002) also analyzed the impact that the Clean Air Act Amendments (CAAA) had on employment in counties that fell under regulation (nonattainment counties). They looked at both plant and industry level data and determined that nonattainment counties lost approximately 590,000 jobs compared to attainment counties. The CAAA cover various pollutants, including carbon monoxide (CO), ozone (O_3), sulfur dioxide (SO_2), and total suspended particles (TSPs). The researcher used a difference-in-difference analysis and found that the effects of these regulations overall had a negative impact on employment growth. These negative effects were still seen when the results were broken down by industry. They also note that industries that emit multiple pollutants faced larger negative impacts than industries that only emitted one pollutant.

Morgenstern, Pizer, and Shih (2002) takes a unique approach to analyzing the impact that environmental policies have on labor market outcomes. Instead of focusing on a policy and using observational data, they utilize Census and plant-level data to observe input prices, outputs, and environmental expenditures to model the structure of production and how it depends on environmental expenditures. They decompose the effects of increased environmental spending into three components: increases in all factor inputs, holding output and factor shares constant (cost effect); changes in factor intensities (factor-shift effect); and changes in the quantity of output demanded (demand effect) (Morgenstern, Pizer, and Shih 2002, 413). The researchers analyzed the impact on increased environmental spending on four heavily polluting industries: pulp and paper; plastics; petroleum; and steel. With plastics and petroleum, they found a small positive impact on employment while in pulp and paper and steel there was no significant effect.

Abrell, Ndoye Faye, and Zachmann (2011) assessed the effectiveness of the European Emission Trading System (ETS) and the impact that it had on firms from 2005 to 2008. Their study is unique because it was the first to look at the entire EU as a whole, rather than focusing on the effects within specific countries. They also use a difference-in-difference analysis to isolate the impact that ETS had on a variety of economic performance indicators, such as employment, profits, and value added. They found that ETS had no significant impact on employment. Since the ETS distributed free permits within its first period, the researchers compared firms that received more emission permits than they needed (over-allocated firms) to ones that received less than they needed (under-allocated). They found that between these different types of firms, over-allocated firms saw their profits increase because of ETS, while under-allocated firms saw their profits decrease. This has important implications for discussing the design of future cap-and-trade policies because it may be a concern that policy makers and citizens have. It is also important to note that RGGI does not distribute free allowances, so this issue should not impact my analysis.

Marin, Marino, and Pellegrin (2018) also looked at the effect that the European ETS had on the economic performance of European manufacturing firms across a panel of EU countries. They specifically use manufacturing firms in their analysis because they are subject to international competition, which may limit a firm's ability to pass-through costs from ETS onto their consumers. These researchers also utilized a difference-in-difference approach to determine the effects of ETS on employment. They found that in the first phase of ETS, there was a small, weakly significant, negative effect on employment, but that effect disappears in the second phase of ETS.

Section 3b

Huang and Zhou (2019) examine how RGGI has decreased CO_2 emissions in the policy region and how this reduction was achieved. The authors describe the five ways that power plants could have reduced their CO_2 emissions: switching to a fuel with a lower carbon content; switching to a non-fossil fuel; improving energy efficiency during generation; sponsoring carbon offset projects; and generation leakage to non-RGGI states. Generation leakage means that the production of electricity is shifted to states that are not regulated and so do the emissions. With leakage, emissions within the RGGI region would appear to be decreasing while emissions in nearby states may be increasing to compensate for the RGGI region's lack of generation. The researchers determined that generation leakage was the main avenue through which RGGI achieved its emission reductions. They used a difference-in-difference analysis to determine the effect of RGGI on utility generation. Their control group consisted of states that were still in the Pennsylvania-New Jersey-Maryland energy market but did not neighbor RGGI states. They found that coal-only utilities significantly reduce their utilization as a result of RGGI, while percent utilization increases in natural gas-only utilities, but the result was statistically insignificant so it is not caused by RGGI. In flexible utilities, ones that could use coal or natural gas, RGGI has no significant impact on their capacity.

Huang and Zhou (2019) then examines the emission reductions caused by RGGI. They find that in Delaware and Maryland CO_2 emissions were reduced by 19.10% of the average total potential annual emissions in those two states. However, based on the previous analysis of utilities, they determined that these reductions were achieved through leaking electricity generation to outside of RGGI states, instead of switching to fuels with lower emissions or investing in energy efficiency technology.

As mentioned in Section 2, Fell and Maniloff (2018) also examine the effectiveness of RGGI on reducing CO_2 emissions. Using a difference-in-difference analysis similar to Huang and Zhou (2019), they find that the emissions reductions in the RGGI region are attributable to generation leakage to other states, but that the leaked energy generation was generated using a less emission intensive fuel, namely, natural gas. This contributed to a net emission reduction even though leakage occurred. They analyzed the impact that RGGI had on both the policy region of RGGI and what they call "leaker regions", Pennsylvania and Ohio. Their results show that the daily capacity of natural gas generators increased by 10 to 15% in leaker regions, while there was no significant change in the RGGI region in natural gas power plants. The daily capacity of coal-fired powerplants in the RGGI region decreased by 9% due to RGGI.

Kim and Kim (2016) attempt to show that RGGI increased the rate of coal to natural gas switching in electricity generation. They use a synthetic controls model to compare the RGGI region to a synthetic RGGI region generated from trends from the rest of the US (excluding Alaska and Hawaii). They find that the implementation of RGGI increased the share of natural gas in the policy region by 10 to 15% compared to the synthetic control region. This result suggests that RGGI accelerated the coal to gas switching rate in the region.

Chan and Morrow (2019) use a difference-in-difference analysis to determine the effect that RGGI has had on CO_2 emissions and other co-pollutants. Their results are consistent with the previous literature mentioned, finding that the reduction in coal energy generation in the RGGI region was replaced by energy generation outside of the RGGI region with cleaner fuels, such as natural gas. Therefore, leakage was still the main source of emission reductions, but the environmental harm of leakage was mitigated through fuel switching. They also found that RGGI caused a significant reduction in sulfur dioxide (SO_2) emissions from the policy region, which has many beneficial health impacts.

These papers are important for my research because they provide a framework for how to perform a difference-in-difference analysis with regards to the impacts of RGGI. They also provide a potential explanation for why there may be no impacts on the labor market because of RGGI. If electricity generation is leaked to other states instead, electricity prices may not be affected and input costs for firms may not increase because of RGGI.

As shown, much research has been done regarding the impact of other environmental policies on labor market outcomes and the impact of RGGI on emissions. However, there is little literature on the impact that RGGI has on labor market outcomes. Informed by these papers, I will expand their frameworks to examine the effect RGGI has on employment.

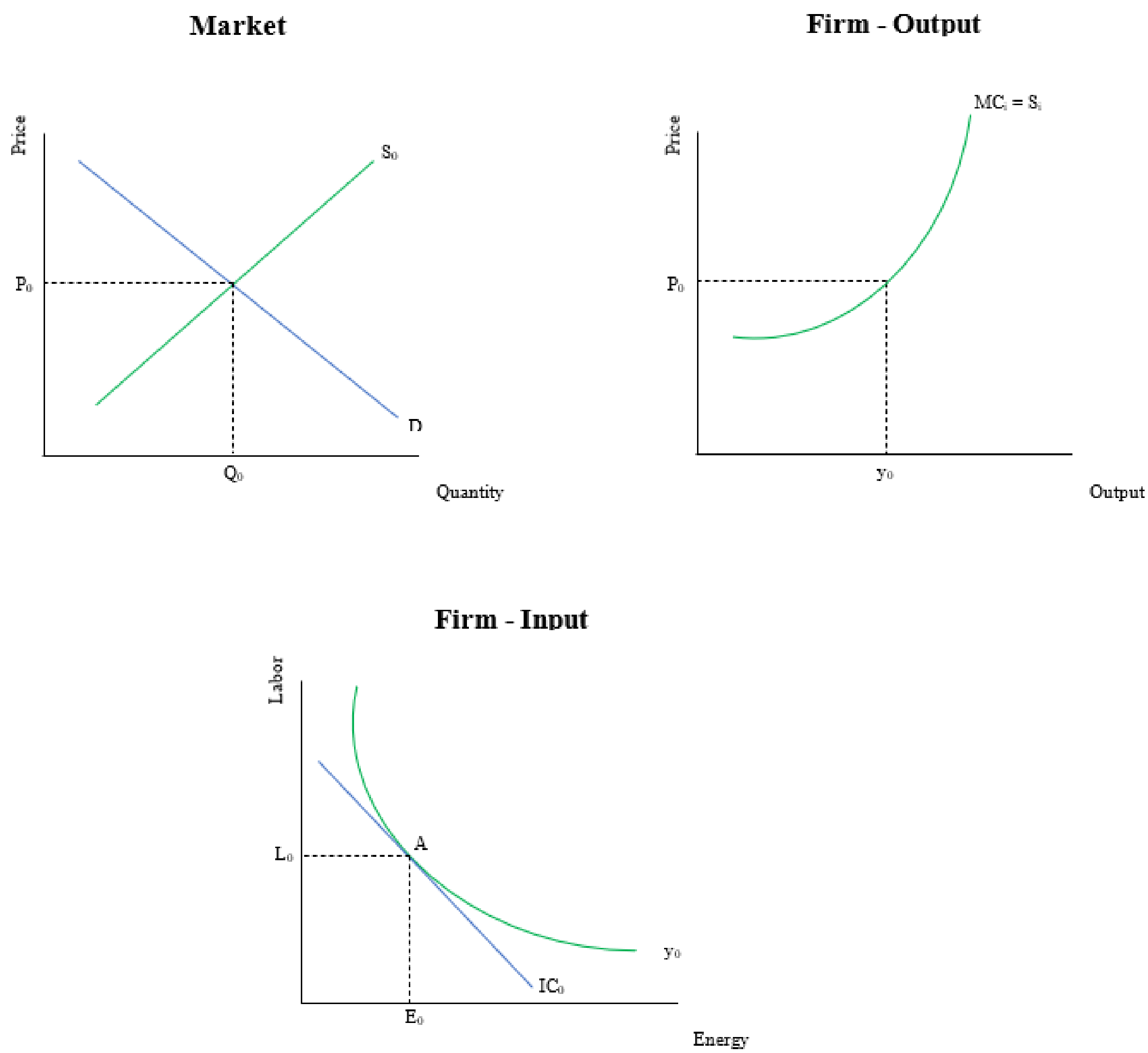
Section 4 – Theoretical Model

To analyze the effect that RGGI has on labor market outcomes, I utilize a simple model to depict the various changes that occur within a competitive market structure. This model represents a market that uses electricity, such as manufacturing. This market would be impacted by RGGI when the electric utility industry passes through the cost of CO_2 allowances to electricity prices. Therefore, electricity is an input. There are three factors that need to be considered to show the impacts that a policy has on employment. They are market supply and demand; individual firm output; and individual firm input.

As shown in Figure 2, the market demand and supply curve intersect when at equilibrium, setting the market equilibrium price (P_0) and quantity (Q_0) for a manufacturing good. At the individual firm level, the firm's marginal cost curve (MC_i) is equivalent to its individual supply curve (S_i). The equilibrium price at the market level determines the output at the individual firm level (y_0). The individual firm's output level then determines its input levels, represented by the isoquant curve in the Firm Input graph. The isoquant curve graphs the different combinations of labor and electricity input that will yield the firm's output level, y_0. In addition to the isoquant curve, there is an iso-cost (IC_0) curve on the Firm Input graph. This line represents the various combinations of electricity and labor input quantities that yield the same total cost of production. The point where the iso-cost curve is tangent to the isoquant curve determines the equilibrium quantity of labor input and electricity input.

When a policy like RGGI is implemented, the curves in these three graphs will shift. For an individual firm, the marginal cost curve will increase because the input of electricity increases in price. Hintermann (2016) shows that utility companies in the EU nearly completely pass on the cost of the emission allowance to their electricity consumers, increasing electricity prices.

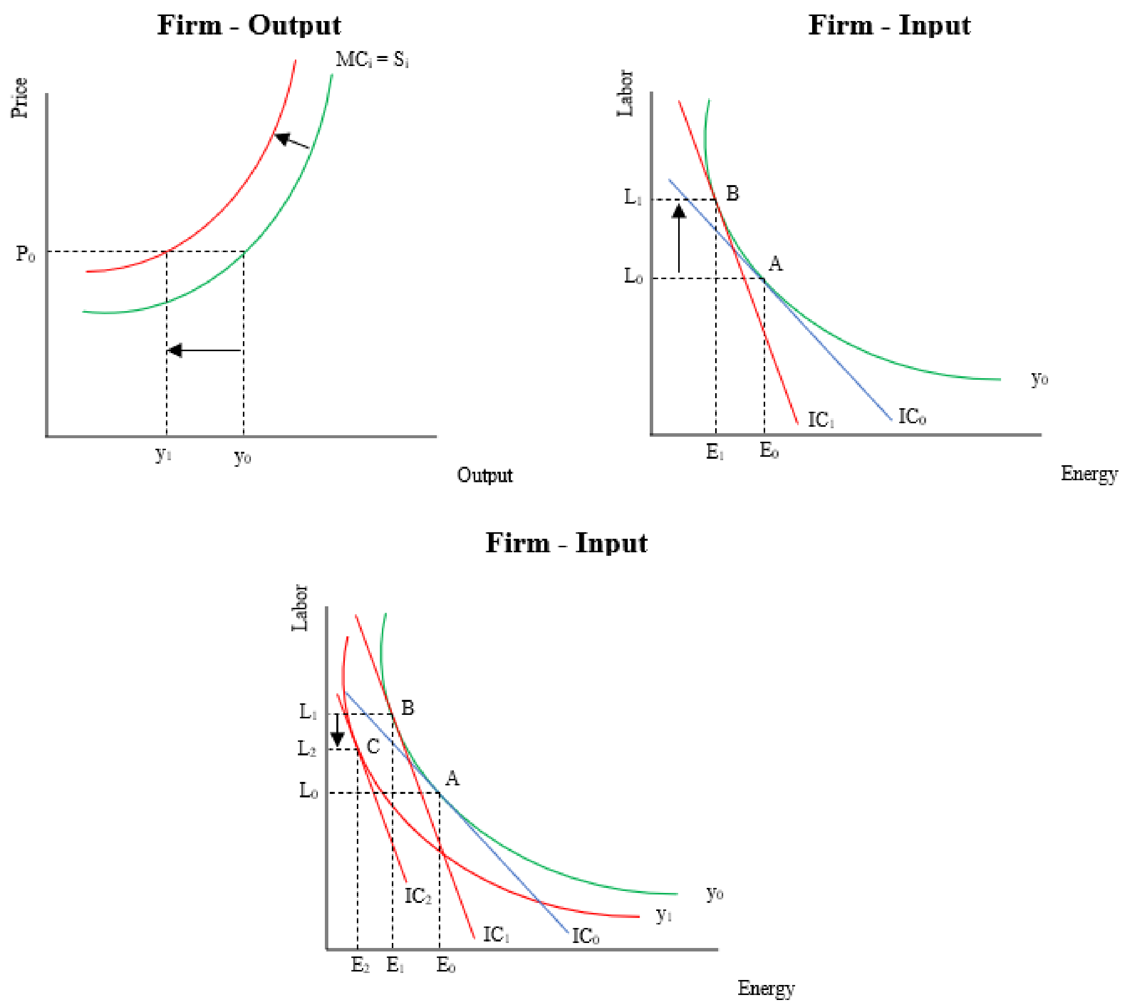
Figure 2: Perfectly competitive market in equilibrium.



As shown in Figure 3, at P_0 the new MC_i creates a new optimum output for the individual firm, labeled y_1. This makes the firm's iso-cost curve steeper on the Firm Input graph. This steeper iso-cost curve actually increases the labor input within the firm, which is referred to as the factor-substitution effect. This is shown by the movement from point A to point B. However, since the firm is producing a different output due to the increased marginal cost, a new isoquant curve needs to be drawn, labeled y_1. Since the iso-cost curve is a part of a series of curves that can be applied at different output levels, we can view IC_2 on the new isoquant curve, y_1. The new point of tangency, point C, shows the final effect of RGGI. The decrease in labor input from point B to point C is called the output effect. The change in labor input from point A to point C is the total effect of the policy, and while these graphs show a slight increase in labor input, the size of these changes and overall direction cannot be determined through theory alone.

Since increasing electricity prices impact all firms within an industry, the market supply curve will also shift (S_1). This shift causes the equilibrium quantity and price to move to Q_1 and P_1. This new equilibrium price will impact the output of an individual firm, shifting it from y_1 to y_2.

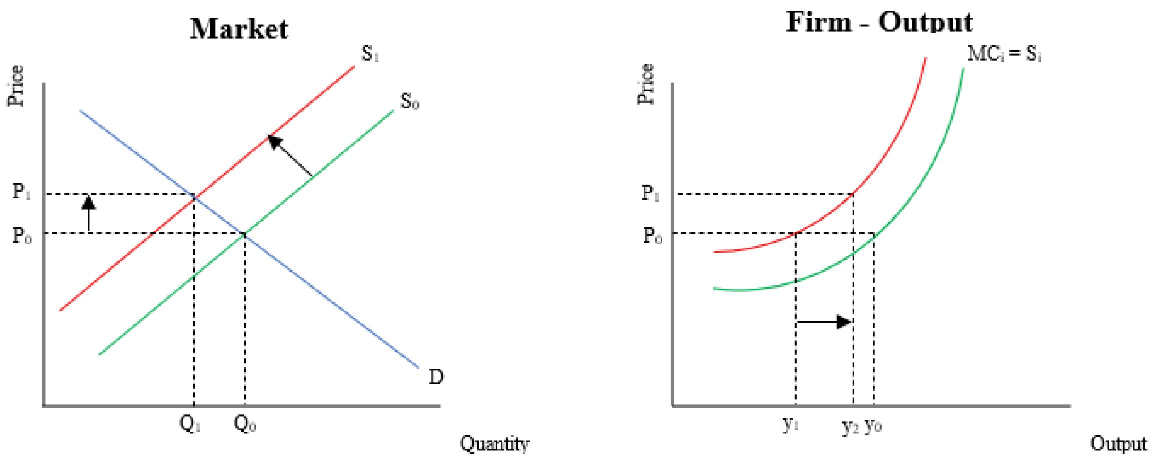
Figure 3: Perfectly Competitive Market looking at individual firm after environmental policy has been implemented.



This increase in equilibrium market price somewhat offsets the initial decrease in output attributable to the increase in marginal cost.

This change in output will again cause the iso-cost and isoquant curves to move, which is

Figure 4: Perfectly Competitive Market and firm effects from environmental policy.



reflected in Figure 4. Therefore, the total effect of an environmental policy from the factor-substitution effect and output effect are ambiguous. This is why further empirical analysis is needed to determine the size and direction of the effects.

Section 5 – Empirical Analysis

Section 5a – Data

I examined the effect of RGGI on labor market outcomes by obtaining employment data from the Bureau of Economic Analysis. These data were available annually by state and industry using the 2002 North American Industry Classification System (NAICS). My dataset consisted of 21 industries, 16 states, and 18 years (2001-2018). I used data from 2001 to 2018 because that allowed for me to have data from eight years before RGGI began and ten years after RGGI was implemented. These data are from the Bureau of Economic Analysis reported the number of jobs for each year by state and industry, but for my analysis I used the annual change in employment.

I calculated this by the natural log of time *t* and subtracting it by the natural log of time *t-1* (Simon 1998). I use this as my dependent variable because there is a large size differential between my control and treatment groups. Using the annual employment growth rate normalizes the two groups. It is also similar the dependent variable that Greenstone (2002) uses. Table 1 shows the descriptive statistics for total employment and the covariates that I use to control for other effects. Table 2 show the descriptive statistics for employment growth rate over the specified time period. Table 2 is also broken down by Industry Type. According to the U.S Energy Information Association farming, mining, utilities, construction, manufacturing, and transportation are the most energy intense industries within the United States. Based off of this, Energy Intense Industries are the ones listed above and Non-Energy Intense are any industries not included. Table 3 and Table 4 show the descriptive statistics for employment growth rate from before RGGI was implemented and after RGGI was implemented. These tables are also specified by industry energy intensity.

The data that I used for my wage covariate were also obtained from the Bureau of Economic Analysis. Annual wages were reported by both state and industry utilizing the same NAICS code as my employment data, which allowed me to manually merge the two datasets. I included industry-specific wage in time *t-1* as a measure of labor costs (Greenstone 2002). Other covariates that I included are share of unemployment in time *t-1*; educational attainment by share of population; share of population in public housing; share of population using lunch subsidies; share of population using rent subsidies; share of population with less than two children; share of population using food stamps; share of population by race; share of population by gender; and share of population by age. These covariates are included to control for any changes that occur over time across states that is not picked up by state fixed effects. I obtained these data from the Integrated Public Use Microdata Series Current Population Survey.

Table 1: Descriptive Statistics (2001-2018)

	N	Mean	Std. Dev.	Min	Max
Control					
Employment	2646	226050.28	229529.93	2836	1129436
Wage	2499	8114635.4	10136381	22653	53087784
Share of Unemployment	2499	.032	.009	.015	.059
Share of Higher Edu	2646	.172	.039	.098	.283
Share of Public Housing	2646	.025	.008	.007	.063
Share of Food Stamp	2646	.113	.04	.039	.216
Share of Pop. Black	2646	.118	.049	.034	.208
Share of Pop. Male	2646	.49	.002	.483	.495
Share of Pop. Other	2646	.032	.02	.008	.081
Share of Pop. Ages 10-14	2646	.066	.005	.057	.075
Share of Pop. Ages 15-19	2646	.068	.004	.059	.075
Share of Pop. Ages 20-44	2646	.334	.017	.301	.379
Share of Pop. Ages 45-64	2646	.263	.015	.221	.292
Share of Pop. Ages 65+	2646	.143	.019	.112	.2
RGGI					
Employment	3326	132020.17	227441.52	185	1773596
Wage	3141	5695364.2	12139455	276	1.230e+08
Share of Unemployment	3213	.03	.01	.014	.065
Share of Higher Edu	3402	.225	.038	.15	.31
Share of Public Housing	3402	.034	.016	.012	.075
Share of Food Stamp	3402	.094	.04	.024	.178
Share of Pop. Black	3402	.115	.098	.007	.32
Share of Pop. Male	3402	.487	.004	.481	.496
Share of Pop. Other	3402	.046	.023	.015	.105
Share of Pop. Ages 10-14	3402	.064	.006	.054	.076
Share of Pop. Ages 15-19	3402	.07	.004	.058	.079
Share of Pop. Ages 20-44	3402	.33	.02	.289	.373
Share of Pop. Ages 45-64	3402	.274	.02	.228	.312
Share of Pop. Ages 65+	3402	.146	.019	.113	.206
Total					
Employment	5972	173681.87	233079.07	185	1773596
Wage	5640	6767307.2	11358637	276	1.230e+08
Share of Unemployment	5712	.031	.009	.014	.065
Share of Higher Edu	6048	.201	.046	.098	.31
Share of Public Housing	6048	.03	.014	.007	.075
Share of Food Stamp	6048	.102	.042	.024	.216
Share of Pop. Black	6048	.116	.081	.007	.32
Share of Pop. Male	6048	.488	.004	.481	.496
Share of Pop. Other	6048	.04	.023	.008	.105
Share of Pop. Ages 10-14	6048	.065	.005	.054	.076
Share of Pop. Ages 15-19	6048	.069	.004	.058	.079
Share of Pop. Ages 20-44	6048	.332	.019	.289	.379
Share of Pop. Ages 45-64	6048	.269	.019	.221	.312
Share of Pop. Ages 65+	6048	.144	.019	.112	.206

The measure of Employment in this table is number of jobs. N is the number of observations.

Table 2: Employment Growth Descriptive Statistics by Region and Industry (2001-2018)

Industry Type	Statistics	Control Region	RGGI
Non-Energy Intense	N	1905	2452
	Mean	.01	.011
	SD	.029	.043
	Min	-.141	-.297
	Max	.165	1.123
Energy Intense	N	741	874
	Mean	-.003	-.001
	SD	.053	.066
	Min	-.206	-.439
	Max	.235	.361

The measure of this table is employment growth: $\Delta \ln(employment) = \ln\,(employment)_t - \ln\,(employment)_{t-1}$.
N is the number of observations.

Table 3: Employment Growth Descriptive Statistics Pre-RGGI by Region and Industry (2001-2008)

Industry Type	Statistics	Control Region	RGGI
Non-Energy Intense	N	765	987
	Mean	.015	.015
	SD	.031	.051
	Min	-.121	-.297
	Max	.165	1.123
Energy Intense	N	324	407
	Mean	-.004	-.002
	SD	.047	.061
	Min	-.162	-.243
	Max	.206	.361

Table 4: Employment Growth Descriptive Statistics Post-RGGI by Region and Industry (2009-2018)

Industry Type	Statistics	Control Region	RGGI
Non Energy Intense	N	1097	1372
	Mean	.007	.009
	SD	.027	.036
	Min	-.141	-.204
	Max	.156	.545
Energy Intense	N	460	560
	Mean	-.002	0
	SD	.057	.07
	Min	-.206	-.439
	Max	.235	.329

In the pre-RGGI time period, annual employment growth in energy intense industries in the control region and RGGI region were decreasing by 0.4% and 0.2% respectively. After RGGI was implemented, the average annual employment in the control region continues to decrease, while average annual employment within the RGGI region is 0.

It is important to note that New Jersey was excluded from my data. New Jersey withdrew from RGGI in 2012 and rejoined in 2020. If included, New Jersey would only experience the treatment for three years of the ten treatment years. Therefore, excluding New Jersey allows for my analysis to have a consistent treatment group. All of the active RGGI states during this time period make up my treatment group, minus New Jersey. My control group is comprised of states with the Pennsylvania-New Jersey-Maryland (PJM) electricity market that are not a part of RGGI. These states include Pennsylvania, Virginia, West Virginia, Ohio, Kentucky, Indiana, and Illinois. I chose these states for my control group because they are similar to the RGGI region in terms of employment composition and being a part of the same electricity market allows for low cross-border trading costs (Huang and Zhou 2019).

Section 5b – Methods

This section discusses the econometric design of estimate the employment effect of RGGI. The simple model illustrated that the total employment effects are determined by two effects: the factor substitution effect and output effect. These two effects make the overall theoretical effect ambiguous. Therefore, using available data I attempt to estimate the total effect of RGGI using the following difference-in-difference equation:

$$Y_{ist} = \beta_1 After_t * RGGI_s + \beta_2 \boldsymbol{X_{st}} + \tau_s t + \delta_i + \alpha_s + \gamma_t + \varepsilon_{ist} \qquad (1)$$

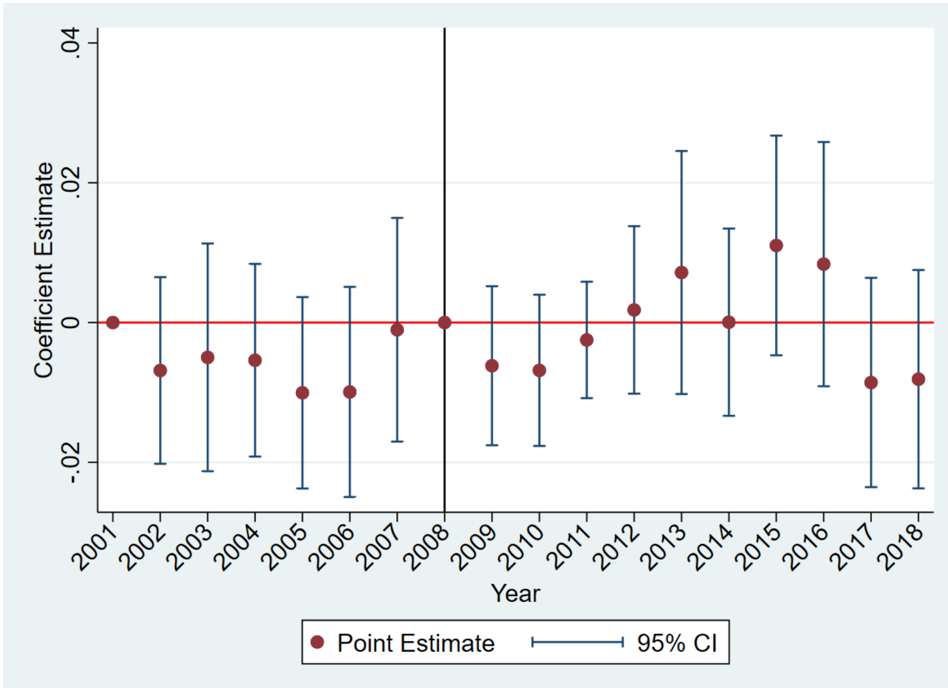
where Y_{ist} is employment growth measured by $\Delta \ln(employment) = \ln(employment)_t - \ln(employment)_{t-1}$, $\tau_s t$ is a state-specific time trend, δ_i is industry fixed effects, α_s is state fixed effects, γ_t is year fixed effects, and ε_{ist} is the error term. $\boldsymbol{X_{st}}$ is a vector of variables that measure differences between states over time. $\boldsymbol{X_{st}}$ includes all of the covariates listed in Section 5a. β_1 is the difference-in-difference estimator for the interaction term between the post variable *After*$_t$ and the dummy variable for RGGI, *RGGI*$_s$. $\beta_1$represents the effect that RGGI has on the annual employment growth rate. To obtain the effect by industry, I run equation (1) with only the data for each specific industry and drop the industry fixed effects while still including the other fixed effects and time trends. I include the state-specific time trend ($\tau_s t$) in order to better capture the different recoveries across states from the Great Recession because RGGI and the Great Recession occurred at the same time. While I do attempt to include controls for these factors within my difference-in-difference regressions using covariates, fixed effects, and time trends, there may still be a bias that is unaccounted for that impacts my coefficient for estimating the impacts of RGGI.

A critical aspect of a difference-in-difference analysis is to show estimates for the treatment group in the periods before the policy was implemented and afterwards. This will verify that there are no differential pre-trends and show that the coefficients are based off of changes that occur when the policy was implemented. I estimate the event study using the following equation:

$$Y_{ist} = \sum_{-8}^{9} \partial_j 1(\rho_{st} = j) + \pi_2 \boldsymbol{X_{st}} + \tau_s t + \delta_i + \alpha_s + \gamma_t + \varepsilon_{ist} \qquad (2)$$

where ρ_{st} indicates the event year, which takes a value equal to one when an observation is j years away from when RGGI was implemented. These event dummy variables replace the $After_t * RGGI_s$ treatment dummy from equation (1). ρ_{st} indexes these dummy variables for years relative to the implementation of RGGI such that $\rho_{st} = 0$ denotes the year that RGGI began. Period -1 is the reference period. The vector $\boldsymbol{X_{st}}$ includes all control variables in the specification described above. Figure 5 plots the coefficients determined from equation (2).

Figure 5: Event Study for Coefficient on Employment Growth Rate



The trends before the implementation a RGGI are fairly constant, which shows a lack of pre-trends in the annual employment growth rate. After 2009, the coefficient increases and even turns positive.

I use Stata/SE 16.1 to run my difference-in-difference analysis.

Section 5c – Results

Table 5 shows the results for equation (1) overall and for specific industries. Column (1) Total shows the results from equation (1) with no industry specification, which is the overall effect of RGGI. These results shows that there is no effect of RGGI on employment growth. This is consistent with results regarding the labor market impact because of other environmental regulations from Berman and Bui (2001), Abrell, Ndoye Faye, and Zachmann (2011), Yamazaki (2017), and Marin, Marino, and Pellegrin (2018).

Table 5 also reports the estimates for the industry-specific effects of RGGI from equation (1) in columns (2) through (16). These estimates, as well as the total effect, are estimated with standard errors that are clustered by state. The weakly significant negative coefficient on mining is consistent with the results from Yamazaki (2017), who showed that energy intense industries are more impacted by environmental regulations than non-energy intense industries. Since RGGI is most likely to impact energy prices, it is reasonable that employment in an energy intense industry would be impacted. The statistically significant coefficients for finance and accommodation services are less easily understood through the framework of RGGI, which could be arising from unobserved factors that are being absorbed into the coefficient for the effect of RGGI. While I used covariates and fixed effects to attempt to capture the effect of RGGI for a causal interpretation, there still may be unobserved factors. For example, my results may be biased if the data do not properly control for the employment effects of the Great Recession because the impacts differed between the control and treatment groups.

It is important to note that the lack of an overall significant impact on the employment growth rate does not mean that individual industries were not impacted. This result is masking the significant heterogeneous impacts at the industry level. Based on my results, it appears that implementing RGGI has caused a decrease in the annual employment growth rate of the mining industry by 0.09 percentage points. That being said, most industries were unaffected by the implementation of RGGI.

Table 5: Difference-in-Difference Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Total	Mining	Utilities	Cons	Manu	WT	Trans	Fin	RE	Prof	Admin	Edu	HC	Acc	Service	Gov
β_1	-.001	-.09*	.014	-.016	.014	.008	0	-.013**	.005	-.007	-.006	.001	.005	.011**	-.008	-.005
	(.003)	(.043)	(.017)	(.012)	(.008)	(.006)	(.013)	(.006)	(.006)	(.006)	(.007)	(.005)	(.003)	(.004)	(.005)	(.004)
R^2	.213	.861	.656	.89	.927	.921	.874	.883	.931	.853	.83	.669	.633	.85	.885	.659
N	5618	230	270	266	272	272	270	272	272	272	272	272	272	272	270	272
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind FE	Yes	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

All regressions include state-specific time trends and covariates that vary by state and over time.

All regressions are weighted by average state population.

Cons stands for Construction; Manu stands for Manufacturing; WT stands for Wholesale Trade; Trans stands for Transportation; Fin stands for Finance; RE stands for Real Estate; Prof stands for Professional Services; HC stands for Health Care; Acc stands for Accommodation Services; and Service stands for Other Services.

Other industries not included in this table are Farming, Forestry, Retail Trade, Information, Management of Companies, and Arts.

Industries that are not included in this table had no significant impacts on their employment growth rates.

Section 5d – Robustness Checks

This paper has attempted to estimate the causal effect of RGGI on employment. Even with a perfect econometric design, non-experimental research might be vulnerable to unobserved variations that could confound the causal interpretation. To ensure the reliability of the estimates, I probed the robustness of the estimates through utilizing different control regions. I find consistency with my previous results for a decrease in mining employment, but the other results vary slightly between different control regions. This suggests that the specifications and data in my analysis could be altered in order to improve the robustness of the results.

Table 6 and Table 7 show the results from my difference-in-difference analysis using two different control groups. Table 6 drops Pennsylvania and Ohio from the control group because they are what Kim and Kim (2016) specify as “leaker states” for electricity generation for the RGGI region. The results for Mining and Accommodation Services are consistent with the results from Table 5. However, this regression shows a weakly significant increase in annual employment growth for the entire policy region because of RGGI. Forestry, Wholesale Trade, and Real Estate also show significant impacts on employment growth because of RGGI, which were not present in the regression from Table 5.

Table 7 uses only states that neighbor the RGGI region as the control group. Again, the result for the Mining industry is consistent with the results from my original analysis. However, from this analysis the weakly significant impact on the overall policy region is negative, which is different from the results in Table 5 and Table 6. Many other industries also show a significant impact on annual employment growth that Table 5 and Table 6 did not show.

Table 6: Difference-in-difference Result Dropping Pennsylvania and Ohio

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
	Total	Farm	For	Min	Util	Con	Man	WT	RT	Tran	Info	Fin	RE	Pro	Mng	Adm	Edu	HC	Arts	Acc	Serv	Gov
β_1	.003*	.005	.026**	-.062**	.017	-.006	.006	.012*	.001	-.011	.004	-.01	.01*	-.005	-.019	-.008	.004	.004	.005	.017***	-.008	-.003
	(.001)	(.015)	(.011)	(.025)	(.01)	(.011)	(.01)	(.007)	(.003)	(.007)	(.011)	(.006)	(.005)	(.008)	(.018)	(.007)	(.008)	(.003)	(.009)	(.004)	(.005)	(.004)
N	4904	238	199	196	236	232	238	238	238	236	236	238	238	238	238	238	238	238	238	238	236	238
R^2	.211	.461	.816	.873	.614	.886	.92	.907	.899	.876	.789	.895	.929	.843	.387	.799	.626	.592	.613	.834	.893	.664
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind FE	Yes	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No

Control Region: Illinois, Indiana, Kentucky, Virginia, West Virginia

Treatment Region: All 2009 RGGI states (excluding New Jersey)

All regressions include state-specific time trends and covariates that vary by state and over time.

All regressions are weighted by average state population.

Farm stands for Farming; For stands for Forestry; Min stands for Mining; Util stands for Utilities; Con stands for Construction; Man stands for Manufacturing; WT stands for Wholesale Trade; RT stands for Retail Trade; Tran stands for Transportation; Info stands for Information Services; Fin stands for Finance; RE stands for Real Estate; Pro stands for Professional Services; Mng stands for Management of Companies; Adm stands for Administrative Services; HC stands for Health Care; Acc stands for Accommodation Services; and Serv stands for Other Services.

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 7: Difference-in-difference Result Using Only Neighboring States in the PJM Energy Market

	(1) Total	(2) Farm	(3) For	(4) Min	(5) Util	(6) Con	(7) Man	(8) WT	(9) RT	(10) Tran	(11) Info	(12) Fin	(13) RE	(14) Pro	(15) Mng	(16) Adm	(17) Edu	(18) HC	(19) Arts	(20) Acc	(21) Serv	(22) Gov
β_1	-.004*	-.006	.018	-.132**	.004	-.019	.001	.002	-.001	-.009	.009	-.016***	.014*	-.016**	-.027	-.006	-.001	.008**	.001	.012	-.01*	-.011*
	(.002)	(.012)	(.012)	(.055)	(.022)	(.01)	(.01)	(.005)	(.004)	(.009)	(.01)	(.005)	(.007)	(.007)	(.016)	(.007)	(.006)	(.003)	(.012)	(.007)	(.005)	(.006)
N	4190	204	165	162	202	198	204	204	204	202	202	204	204	204	204	204	204	204	204	204	202	204
R^2	.212	.469	.897	.873	.65	.894	.943	.929	.891	.876	.818	.889	.929	.842	.429	.817	.562	.613	.576	.834	.878	.706
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind FE	Yes	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No

Control Region: Pennsylvania, Virginia, and West Virginia

Treatment Region: All 2009 RGGI states (excluding New Jersey)

All regressions include state-specific time trends and covariates that vary by state and over time.

All regressions are weighted by average state population.

Farm stands for Farming; For stands for Forestry; Min stands for Mining; Util stands for Utilities; Con stands for Construction; Man stands for Manufacturing; WT stands for Wholesale Trade; RT stands for Retail Trade; Tran stands for Transportation; Info stands for Information Services; Fin stands for Finance; RE stands for Real Estate; Pro stands for Professional Services; Mng stands for Management of Companies; Adm stands for Administrative Services; HC stands for Health Care; Acc stands for Accommodation Services; and Serv stands for Other Services.

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

These results suggest that the inclusion of different states in the analysis does affect the analysis of the employment effect of RGGI. This is always a concern when using a simple difference-in-difference analysis. Without proper specifications to control unobserved variables, the differences estimator can be impacted by events that occurred simultaneously with RGGI. For future analyses, it will be important to introduce more controls for these unobserved variables in order to attain more robust results.

Section 6 – Discussion and Conclusion

This paper provides evidence that a carbon cap-and-trade policy had no effect on employment. The existing literature provides mixed findings on how an environmental regulation affects employment in a regulated region, and no existing papers have looked at the impact that RGGI has had on employment. Using a difference-in-difference analysis, this paper found that overall RGGI had no impact on employment. However, when analyzed at the industry level, RGGI had a weakly significant negative impact on employment within the mining industry.

While these results are consistent with other studies that have shown environmental policies that have no effect on the labor market, there is still more research that can be done on the impacts of RGGI. Gathering plant-level data may provide a more concrete view of the way that RGGI has affected employment. It would also be beneficial to determine the true pass through price from emissions allowances to electricity because that is the main avenue through which RGGI would impact industries outside of the utility sector. In future analyses, it will also be important to control for other policies that might impact labor market outcomes during the time period that RGGI was implemented.

An analysis that looks at the redistribution effects of RGGI would also provide a more in depth look at how RGGI impacts the labor market. As Yamazaki (2017) showed, the redistribution effect of the BC carbon tax was the aspect of the policy that generated the most growth in employment. An analysis of how each state utilizes their revenue from the auctions of CO_2 allowances was too large for the scope of this project. That type of analysis would provide insight into why there have not been larger declines in employment, especially within energy intense industries. It may also provide suggestions for how states could improve their allocation of the revenue in order to decrease the effects that RGGI may have on energy intensive industries, such as mining.

It is also important to consider how these results relate to issues of environmental and social justice. While there may be no overall effect of the policy, people and communities whose economic livelihoods depend on energy intensive industries may be adversely impacted by RGGI and similar environmental policies. Curtis (2014) shows that another cap-and-trade program, the NO_x Budget Trading Program, negatively impacted employment in the manufacturing sector. They also found that young employees were the hardest hit in terms of increased unemployment and decreased wages. A future research paper might determine which demographics are most impacted by a carbon cap-and-trade policy, like RGGI, and how the policy can be revised to mitigate such effects.

Another future research project might be to take this analysis of the labor market further and create a holistic argument about the effect of RGGI on employment. This research would entail looking at the extent to which the increase in energy prices from RGGI triggers substitution to renewable sources of electricity that could in turn generate jobs in the renewable energy sector. That being said, my study only goes as far as analyzing the impact that the increased energy prices from RGGI have had on employment growth rates. My analysis has shown that the increase in input cost has not significantly impacted the employment growth rate within the majority of industries, with the exception of mining, an energy intense industry. If these results are indicative of the true relationship between RGGI and its labor market outcomes, it supports previous studies that showed environmental regulations did not have a negative impact on employment.

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